

Effects of Entry Economic Conditions on the Career of Economics Ph.D.

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November, 2021

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Abstract

Bad labor market conditions at the entry have large and persistent negative effects on careers in general, but evidence of the impact on the economist is scarce. I estimate the effect of entry economic conditions on the careers of economics Ph.D. recipients from the top 32 programs in the U.S. who graduated between 2004 and 2012. I use natural language processing (NLP) to match degree holders with the career information scraped from various data sources. A simple theoretical model of task-specific human capital formation reveals the possible mechanisms driving the permanent effect of the entry condition on their careers. I empirically test the model's predictions using nearly complete employment histories and find that entry conditions cause an occupational mismatch at graduation. Poor entry conditions are associated with a decreased probability of getting a full-time position in an R1 university in the U.S. both in the short run and long run. I also find that a one standard deviation increase in the unemployment rate would result in 2.31 percent fewer publications. The primary mechanism through which entry conditions have a long-term effect is immobility across occupations.

JEL classifications: J23, J24, J44, J62, I23, I26

Keywords: Recent graduates, Economics Ph.D., Human capital, Mismatch, Job mobility

*I would like to thank the economics department at University of Houston for financial assistance in collecting data. Special thanks to Santosh Kumar for donation to the department. I am immensely grateful to Chinhui Juhn, Vikram Maheshri, Aimee Chin, Willa Friedman, Fan Wang, Yona Rubinstein, Eleanor Jawon Choi, Hugo Jales, Francisca Antman, and Gael Compta for their valuable insight and helpful comments. I also thank seminar/conference participants at University of Houston (2021) and Southern Economic Association 91st Annual Meeting (2021). I am indebted to Elaine M. Liu for her invaluable guidance and support. All remaining errors are mine.

1 INTRODUCTION

In the United States, there has been strong demand for economists over the past decade (Bureau of Labor Statistics 2021). Economists are valued in many industries for their quantitative approach to analyzing business, sales, and market trends. Although many economic indicators signal a bright outlook for the economists, the Covid-19 pandemic revealed that even a profession with such strong labor market fundamentals is not immune to an economic downturn. According to the INOMICS Salary Report 2020, about one-third of economists experienced wage loss, promotion delay, and unemployment worldwide in 2020. The JOE Listings (Job Openings for Economists) for 2020 had 14 percent fewer job postings than in 2019. Given that young workers are particularly vulnerable to unfavorable economic conditions (Elsby, Shin, and Solon 2016), it raises the question of whether economics Ph.D.s who graduate in recessionary periods face lasting scars.

The labor market for economists has many unique characteristics that allow progress in answering this question. First, there is a *well-defined* job market. Most jobs are posted on the American Economic Association website, and the recruiting process primarily occurs through Allied Social Science Associations (ASSA), which holds a three-day meeting each January in the U.S. Job seekers must have a Ph.D. degree in economics (or in a related discipline). Second, the entry-year unemployment rate is comparatively very low for economists. Most of the new jobs for the new graduates are expected to be in universities, but the placement outcomes vary every year. Third, the workplace environment is vastly different by occupation from other occupations. Academic workers usually work under *up-or-out* policies, in which workers who miss a set of promotion opportunities hardly make it after. Whereas private-sector workers work in high-skilled industries in which job attachments tend to be low. Also, more than half of the job market is filled with international candidates who may prefer to return to their home country after completing their Ph.D. And fourth, productivity is measurable through publishing activity. Academic publications are valued both in academia and practice (Swidler and Goldreyer 1998; Hansen, Weisbrod, and Strauss 1978). Information on economists' productivity could be compiled from the EconLit in which each individual's all journal article publications are listed.

In this paper, I develop a theoretical model of human capital formation building on Gibbons and Waldman (2006) that allows me to jointly study the occupational mobility and productivity of new economics Ph.D.s. I model production as a combination of multiple tasks. Occupations differ according to the tasks they require and the relative importance of each task for production. Workers can acquire task-specific human capi-

tal in different occupations. As a result, to the extent that economic conditions at entry affect the initial placements of workers into occupations, the model has scope for these conditions to affect the trajectories of both mobility and productivity. Because early career change is discouraged in academics or up-or-out environments in general (Gardner and Blackstone 2013), the model predicts the entry condition effects would persist.

I test the predictions of my model with a novel dataset on recent PhD graduates that I collected. I gather information on 4,521 economics Ph.D. that graduated between 2004 and 2012 from 32 Ph.D. granting programs in the U.S. Graduate students are identified from the ProQuest Dissertations & Theses Global.¹ Given their names and dissertations, I locate their CVs on the world wide web. Because these CVs may be in various places (e.g., personal websites, LinkedIn, etc.) I develop an automated algorithm to search the web and leverage natural language processing techniques to better match CVs to dissertations. I am able to match 88 percent of newly minted PhDs.² Furthermore, I define occupations as collections of firms (or placements) that require the same tasks. Since most firms in which economists would work belong to a tiny range of industry codes, I use another index based on various sources, for example, time-usage surveys of faculties or the job descriptions in the JOE. I divide all the placements into five categories: R1 university, all other universities in the U.S., research organizations in the U.S., foreign institutes, and private sectors.

I find the following results from my empirical analysis. First, the demand for economists is pro-cyclical. The overall demand moves in the direction of macroeconomic conditions, and the fluctuations are primarily driven by the job openings in academic tenure-track positions in the US. Second, entering a recession is bad for initial placements. A one standard deviation increase in the unemployment rate has adverse effects on the likelihood of academic employment, quality of initial placements, and productivity as measured by publications. It lowers the likelihood of employment in an R1 university by 9.14 percent on average. This effect declines over time. Conditional on taking an academic job, it lowers the ranking of the initial placement by 8.0 percent. It reduces the number of publications in the top 50 economics journals by 2.31 percent. Third, these effects are primarily mediated through (lack of) mobility. Economists rarely switch occupations in response to changing economic conditions. I find evidence that one determinant of these switching costs is the development of task-specific human capital.

I estimate the effect of entry economic conditions on the careers of economics Ph.D. from 32 U.S. economics Ph.D. programs from 2004 to 2020 following the approach pro-

1. See detail in section 4.

2. See detail in Appendix A.

posed by (von Wachter 2020). There are two main threats to identification in my context. First, a causal interpretation of the estimates requires that the average quality of graduates entering the market is not systematically related to the state of the economy. However, job market candidates would delay graduation in response to the negative shock to the labor market at graduation. My data partially allows me to address this issue since the starting and completion year of Ph.D. are observable for about 60 percent of individuals. I examine whether the entry economic conditions would make the individuals study more than five years, and I find no evidence on the timing of graduation. Second, attrition in my sample would result in attribution bias which may confound my empirical analysis. From the ProQuest database, I am managed to scrape about 80 percent of individuals' career information. Because those missing individuals are plausibly less successful on average, my estimates would provide a lower bound on the effects of entry conditions.

The remainder of the paper is organized as follows: Section 2 surveys related literature and presents how I contribute to them. Section 3 lays out the model of task-specific human capital to examine the implications of job mobility for economists and provides the testable hypothesis. Section 4 presents the overview of data and relevant measures. The demand for the economist is summarized in this section as well. Section 5 discusses the empirical strategy and provides the identifying assumptions. Section 6 empirically tests the model's predictions and discusses the range of results. Section 7 concludes.

2 LITERATURE REVIEW

Job mobility is one of the critical mechanisms to assess the impact of graduating during an economic downturn since making up for lost time would happen through job mobility. Because young workers actively search for well-matched jobs and they often pursue promotion or wage rise through switching a job, mobility plays a significant role in early career growth (Topel and Ward 1992). During recessions, the number of and quality of jobs declines (Altonji, Kahn, and Speer 2016; Liu, Salvanes, and Sørensen 2016). College graduates tend to switch firms or occupations often, and this approach resulted in high gain compared with their counterparts who started in a boom (van den Berge 2018; Cockx and Ghirelli 2016). It is not much known whether Ph.D. graduates would show the same patterns. Another approach for examining this mechanism is how human capital is valued across the firms and occupations (Becker 1994; Mincer 1993). Literature clearly distinguishes general-purpose skills and specific skills required in specific industries for specific occupations. The former is valued almost equally by all firms or sectors, such as education or labor market experience. The specific skills, denoted as occupation-specific,

firm-specific, or task-specific skills, are valued differently by what industry or firms one works at or what tasks one is assigned to (Altonji and Shakotko 1987; Kambourov and Manovskii 2009; Gibbons and Waldman 2006). However, it is not clear what types of human capital economists would develop.

The basic structure of my model is closely related to Gibbons and Waldman (2006). It supplies the intuition of task-specific human capital formation in theory and practice. It highlights the difference between task-specific human capital and occupation-specific (or firm-specific) human capital and explains why wage structure inside firms might have cohort effects. My model applies this idea to the search model. A worker accumulates task-specific human capital, which is the most crucial input in production. I introduce the switching option to the model, and the propositions would supply the intuition of worker's mobility.

The empirical investigation of the extent to which the initial economic conditions affect the economists' career contributes to several distinct literature. The first related body of work analyzes the effects of bad starting conditions at graduation, on persistent labor market outcomes. While immediate effects of entering the labor market in a downturn are expected, many worry that young workers will suffer long-lasting adverse effects. If this is true, this type of hysteresis could point to a lost generation of young workers who will be stuck in mismatches and low-paying jobs. One set of papers studies that people who enter the labor market during a recession indeed receive lower wages even years after the recession period (Brunner and Kuhn 2014; Kahn 2010; Oreopoulos, von Wachter, and Heisz 2012). Microeconomic data such as CPS does not record the year the respondent completes the education and enters the labor market. Therefore, literature employs Mincerian proxy³ for the year of labor entry. The findings imply that hysteresis might be cause for genuine concern, although more recent works find that the effects would vary by the level of education and college major on the wages and unemployment spell (Altonji, Kahn, and Speer 2016; Cockx and Ghirelli 2016; Hershbein 2012; Liu, Salvanes, and Sørensen 2016). Another set of papers within this body of work studies that the young workers in Europe or Japan, with more inflexible labor market compared to the U.S., suffer more from finding a job compared to U.S. workers (Cockx and Ghirelli 2016; Genda, Kondo, and Ohta 2010).

This paper expands this literature by considering the effects beyond college education with detailed data. While some papers have explored the differences between high and low educated workers (Cockx and Ghirelli 2016; Genda, Kondo, and Ohta 2010; Altonji, Kahn, and Speer 2016) no study examines the differential effects for Ph.D. graduates, to

3. The sum of the year of birth, plus six and plus the years of reported education.

the best of my knowledge. Oyer (2006) studies the impact of completing an MBA or an economics Ph.D. during a recession, focusing on graduates from seven departments in the U.S. This paper is different from Oyer (2006) in three ways. First, I include the individuals from 32 Ph.D. programs in the U.S. presenting more general cohort characteristics. Second, nearly complete employment characteristics allow me to trace graduates having non-academic careers. Third, since the early 2000s, the demand from the private sectors and international institutes grew exponentially,⁴ hence the entry conditions in the U.S. would lead to different labor market outcomes than Oyer's.

While the above literature has concentrated on establishing a link between initial entry conditions and future outcomes, the primary focus of this paper is to examine the channel through which these persistent losses occur. Job matching is a process that is always present over the course of a business cycle, so I first analyze whether the match quality between a worker and the initial placement would play a critical role. Many research studies find that job match quality is adversely affected during recessions (Bowlus 1995; Cole and Rogerson 1999; Kahn 2010). Liu, Salvanes, and Sørensen (2016) show that cyclical skill mismatch between college graduates and employers is an essential mechanism behind persistent career loss in Norway. For economics Ph.D. market, assuming they are research-oriented, the mismatch would imply that the graduates started their careers in which the main tasks are not research-related. I observe that R1 universities would value the academic journals more than any other occupations and that the preference would get stronger for the elite schools. Hence, I examine whether the entry conditions would affect R1 university placement records and the ranking of the academic placements.

Job mobility plays a crucial role in recovering from the damages for those who start in a recession (van den Berge 2018; Cockx and Ghirelli 2016). This leads me to analyzing the job mobility of the economists over their careers. Note that the early career changes are discouraged at universities where tenure decisions are made at a fixed point in time. The patterns of job mobility for other occupations where economists work is not entirely known, but I find that the mobility is pretty low compared to other U.S. workers or inflexible labor markets in Europe. In general, an economics Ph.D. has low job mobility, and it raises the question of how it relates to the permanent effects of the entry conditions.

Most papers consider the role of the first firm in explaining the initial and persistent losses empirically (Liu, Salvanes, and Sørensen 2016; Oreopoulos, von Wachter, and Heisz 2012). I approach the question with the task-specific human capital model I built. The task-specific human capital model could provide an explanation for cohort effects since workers are forced to develop their human capital according to the tasks assigned.

4. The number of postings in private sectors from JOE increases about 73 percent between 2004 and 2012.

If it were true, the economic downturn likely has a permanent impact on those who end up at lower-ranked schools or private sectors in which the main tasks are different from research universities. To the best of my knowledge, there is no research applying these theories to the market for economists.

3 THE MODEL

3.1 THEORETICAL FRAMEWORK

In this section, I propose a model to examine the mobility of economists. I build the model based on the concept of task-specific human capital proposed by Gibbons and Waldman (2004, 2006). The purpose of the model is to show how individuals accumulate human capital and how it contributes to the output over time.

I define an occupation o as the collection of firms having the same tasks. A firm f assigns the combinations of tasks $\{1, \dots, J\}$ to a worker. In the case of economists, consider the occupations as research universities, teaching colleges, or private companies in which the main tasks are arguably similar. For example, firms contained within research universities would be doctoral universities in the U.S. where research performance would be valued the most compared to firms within teaching colleges where teaching tasks would be more emphasized. Hence, tasks could range from teaching, research, communication, administrative work, etc., and the emphasis would be different from occupations. If a worker i is hired by firm f within o at t , then the worker i produces the task-specific output Y_{ifot}^j as:

$$\log Y_{ifot}^j = \sum_j \beta_o^j \alpha_{iot}^j + \mu_{if} \text{ where } \sum_j \beta_o^j = 1 \text{ for all } o = 1, \dots, O \quad (1)$$

where α_{iot}^j is i 's productivity for task j for o at t , and μ_{if} represents the match quality between worker i and firm f . Each occupation combines the tasks in different ways, so β_o^j denotes the share of time a worker spends on average for task j in o . In addition to the relationship between i and o , the unobserved match component may affect the output as well. For example, individuals with the same level of productivity hired within occupation o would produce different amounts of outputs since some of them formed better employer matches. μ_{if} characterizes a firm-match component to take into account it.

The worker's productivity α_{iot}^j on task j is determined by the initial endowment of the task α_i^j and the human capital specific to the task accumulated through labor market

experience:

$$\alpha_{i\text{ot}}^j = \alpha_i^j + \gamma_o H_{it}^j \quad (2)$$

where γ_o is the occupation-specific return to human capital. Task-specific human capital H_{it}^j is developed through occupation experience until time t and how much valued by the previous occupation o' :

$$H_{it}^j = \beta_{o', \text{Exp}_{io'/t}}^j \text{ where } \sum_j \beta_{o'}^j = 1 \text{ for all } o' = 1, \dots, O \quad (3)$$

where $\text{Exp}_{io'/t}$ denotes the previous tenure in occupation o' to simplify exposition.⁵ Plugging (2) and (3) into (1) yields

$$\log Y_{i\text{fo}t}^j = \gamma_o \overbrace{\left[\sum_j \beta_o^j \left(\underbrace{H_{it}^j}_{\beta_{o', \text{Exp}_{io'/t}}^j} \right) \right]}^{\text{Task}_{i\text{ot}}} + \underbrace{\sum_j \beta_o^j \alpha_i^j + \mu_{if}}_{\text{Match quality}}^{m_{io}} \quad (4)$$

where $\sum_j \beta_o^j = 1$ for all $o = 1, \dots, O$

Note that $\text{Task}_{i\text{ot}}$ is a measure of task-specific human capital valued by occupation o at t . m_{io} is the match quality between i and occupation o . I assume the match quality with a firm μ_{if} is random and does not develop by time. In sum, the first term, $\text{Task}_{i\text{ot}}$, captures the match quality between acquired human capital and the assigned tasks, the second term, m_{io} captures the match quality between innate ability endowment for an individual and the tasks, and the last term, μ_{if} , capture the match quality between an individual and a firm. The specification captures critical features of the production function in which the human capital is the primary inputs. It assesses the relationship between outputs, occupations, firms, and task-specific human capital an individual developed.

3.2 INCORPORATING ENTRY ECONOMIC CONDITIONS

When a worker enters the market for the first time, there are no human capitals accumulated ($\sum_j H_{it}^j = 0$). I impose two more assumptions to reflect the effect of economic conditions at entry. Among the set of tasks J , denote $j = 1$ as economics-related research.

5. $H_{it}^j = \sum_s^{t-1} \beta_{os}^j$ where $\sum_{j=1}^J \beta_{os}^j = 1$ for all o, s .

Assumption 1

$$\alpha_i \equiv (\alpha_i^1, \dots, \alpha_i^J) \equiv m(X_i) + e_{it}, \text{ where } \alpha_i^1 \geq \max_{j \neq 1} \alpha_i^j$$

The assumption 1 implies that most workers are research-oriented. It is necessary to reflect the pro-cyclical demand for economists. Let \bar{t} and $u_{\bar{t}}$ denote the graduation year of i and economic condition at time of graduation.

Theorem 1

$$\text{If } u_{\bar{t}} < u'_{\bar{t}}, \text{ then } \mathbb{E}_i \left[m_{io} \mid u_{\bar{t}}, \sum_j H_{it}^j = 0 \right] > \mathbb{E}_i \left[m_{io} \mid u'_{\bar{t}}, \sum_j H_{it}^j = 0 \right]$$

It implies that a mismatch between a worker and occupation would arise when the initial economic condition is unfavorable.⁶ Note that m_{io} would be higher if one's innate abilities are well matched to the task assignments. In the case of the economist, economic downturn at graduation would more likely to place the job market candidates at the occupations in the research tasks are less emphasized compared to the good times.

3.3 MOBILITY

Switching firms or occupations for individuals is defined as working at different firms or occupations in year t compared to year $t - 1$. All firms belong to occupations, so individuals can only switch occupations if they also switch a firm. If i does not switch the occupation, the following corollary is derived:

Corollary 1

$$\text{If } u_{\bar{t}} < u'_{\bar{t}} \text{ and } i \text{ did not switch o, then } \mathbb{E}_i \left[Y_{ifot}^1 \mid u_{\bar{t}}, X_i \right] > \mathbb{E}_i \left[Y_{ifot}^1 \mid u'_{\bar{t}}, X_i \right] \text{ for all } t$$

Note that Y_{ifot}^1 is research-task related output. In sum, the gap is driven by the two factors. First, if the economic conditions at entry were bad, the match quality between a worker and an occupation would decline, and hence the initial output gap would arise. From (3), a worker accumulates the task-specific human capital according to the specific occupational experience. Hence, if one did not switch the occupation, the worker is forced to accumulate undesirable human capital, and therefore the output gap would not be closed

6. The theorem is consistent with Bowlus (1995).

over time. In the case of the economists, if one would be placed at teaching colleges or private sectors due to an economic downturn, then the individual is less likely to accumulate research-related skills if one did go back to research universities.

Consider how the task-specific human capital would be valued if a worker switched occupations. For example, intuitively, if one accumulated research-related skills, then her human capital would be valued more in the research-emphasized occupations than teaching-emphasized occupations. To make an exposition simpler, I examine two-task⁷ model $J = \{R, T\}$. As noted above o' and o indicate the source and target occupations, respectively. From the specification (4), I derive the following proposition:

Proposition 1

*For $\beta_{o'}^R > 0.5$, task-tenure is valued more if moves to $\beta_o^R > \beta_{o'}^R$,
For $\beta_{o'}^R < 0.5$, task-tenure is valued more if moves to $\beta_o^R < \beta_{o'}^R$,
For $\beta_{o'}^R = 0.5$, task-tenure does not change regardless of moving*

How the task tenure is valued depends on the degree of specialization in the source occupation. Note that $\beta_{o'}^R = 1$ implies the occupation o' is fully specialized in research and that $\beta_{o'}^R = 0$ implies the occupation o' is fully specialized in teaching. $\beta_{o'}^R = 0.5$ suggests that the occupation o' would not distinguish between the two skills, meaning that the occupation o' is completely general. The proposition presents that if the target occupation is more specialized than the source occupation, the one's task-tenure would be valued more. If the source occupation is very general (close to 0.5), the task-tenure is valued equally by any target occupation, and hence switching does not have any merits. Now let's consider the implication of job mobility

3.4 OCCUPATIONAL CHOICE

Now consider one's occupational choice. In each period, a worker needs to decide to switch the occupation or not. To make an exposition simpler, consider a two-period problem. Suppose an individual i started the career at a firm f' within an occupation o' . In the next period, suppose a firm f within o offers i to move. However, switching the occupation is costly, so that it would generate a switching cost $x_{o't}$. Hence the worker i faces:

$$\max_{o', o} [Y_{if'o't}, Y_{ifot} - x_{o't}] \quad (5)$$

7. For example, research and teaching, or research and all other tasks.

Assuming that o' is research-specialized occupation, an individual i will move to o if $Y_{ifot} - x_{o't} > Y_{if'o't}$. Using (4), rewrite the condition as:

$$\begin{aligned} (m_{io} - m_{io'}) + (\mu_{if} - \mu_{if'}) + (\gamma_o - \gamma_{o'}) \text{Task}_{io't} \\ > \gamma_o \underbrace{\left[\left(\beta_{o'}^R - \beta_o^R \right) \left(H_{it}^R - H_{it}^T \right) \right]}_{\text{potential loss}} + \underbrace{x_{o't}}_{\text{switching cost}} \end{aligned} \quad (6)$$

Improvement on the match qualities and higher returns to task tenure from the target occupation o would make a shift more likely, but there is a loss from the task tenure according to the proposition 1 together with the switching cost $x_{o't}$.

The potential loss is determined by the two factors. First, $\beta_{o'}^R - \beta_o^R$ represents how similar the tasks between the source and target occupations. If the target occupation requires different skill sets, then β_o^R would be different to $\beta_{o'}^R$, and hence the loss would arise. Second, if how much the task-specific human capital is accumulated would affect the size of the loss. It relates to how much one spend time in the target occupation. For example, if one graduate were placed at a teaching college initially. Then, she will accumulate more teaching skills compared to research. The more she stayed at the teaching college, the more skill gaps would be developed.

3.5 BRIEF OVERVIEW OF THE MODEL'S CONTRIBUTIONS

The specification (6) provides the testable implications on the characteristic of human capital for economists. If economists' human capital is not task-specific, the right-hand side of the specification (6) is collapsed to the switching cost since there are no skill gaps. If the initial mismatch happened at entry, the workers would be more likely to switch afterward, hence diminishing the effect of entry conditions in no time. But if the economist's human capital is task-specific, there are two more cases to consider. Firstly, if the economist's tasks are specialized (distance between the occupations are significant), then they would less likely switch because they might risk losing the human capital accumulated from the source occupation. If the initial matching is undesirable, the switching should be made early in their careers because the skill gaps would grow over time. Hence, if the institutional settings would hinder the worker from shifting the occupation in their early career, the initial placement effects would be long-lasting. Secondly, if the economists' human capital is task-specific but the industry is not specialized (distance between the occupation is small), then the right-hand side of the specification (6) is collapsed to the switching cost again; the economists would switch the occupation more

likely if there were an initial mismatch. Hence, the initial placement effects are less likely permanent.

4 DATA AND SAMPLE SELECTION

The data set contains information on Ph.D. students from 32 universities in the United States who achieved the degree from 2004 to 2012. Graduate students are identified from their dissertations posted in the ProQuest database since most doctoral students in the U.S. are required to submit their dissertations to ProQuest, which is the most comprehensive database in the world. ProQuest provides a search tool for finding dissertations. Authorized users can extract the name of the authors, Ph.D. institutions, degree date, advisor names, title, abstract, and range of classifications. Many of the economic-related dissertations are in fact from other departments. For example, a health economist from the school of public health may list their dissertations under economics classifications.⁸ Unfortunately, the authors' department information is available after class of 2013, so I use advisor's information if the classification code does not include economics (0501). I use *googlesearch* library in Python to extract advisors' information whether they are faculty members in the economics department. The total number of individuals is 6,582.

From the dissertations' title, classification, identifier, and subject in ProQuest, I approximate the field of study following JEL classifications. If the title does not clearly indicate the field of study, I count every word in the abstract. Then, I try to find the match between the most frequent word and the field of the study.⁹ Information on employment history for each individual is either taken from the most recent C.V. or the LinkedIn experience profiles.¹⁰ I then convert the employment information into a yearly panel.

I collect the publication records through EconLit. I extract all the articles in the top 50 economics journals listed in *IDEAS/RePEc Simple Impact Factors for Journals* between 2002 and 2020 for my primary analysis.¹¹ Based on the collected articles, I try to find the publication records for each individual.^{12,13}

I group the individuals based on a degree year as a cohort. However, given that one would obtain the degree years after graduation, there would be a mismatch between a

8. The list of departments under the economics classification is economics, business, agricultural economics, health economics, political science, politics, sociology, mathematics, and statistics.

9. See appendix A

10. See appendix A

11. See the list of journals on <https://ideas.repec.org/top/top.journals.simple.html>

12. ProQuest does not allow an individual access to scrape the publication records. However, the total journal articles information is downloadable.

13. See appendix A

degree year in dissertation and graduation year in C.V. If this is the case, I use the graduation year instead of the degree year when labeling the individuals. In sum, I observe name, degree date, Ph.D. institution, bachelor institution, career history, gender¹⁴, fields of study, and publication records for each graduate.

To explore the demand for an economist, I purchase the number of listings in Job Openings for Economists (JOE) during the years from the American Economic Association. It contains the title of the job, position, location, JEL classification, and the description of the job. It is posted monthly except in January and July. I convert it into a yearly panel based on an academic year. For example, the demand in 2004 consists of the listings in 8, 9, 10, 11, 12 in 2003 and 2, 3, 4, 5, 6 in 2004.

In the section 3, I define the occupation as the collection of firms having the same tasks. Change in occupation means that the skills required for new occupations would be substantially different from those used in the old occupations. Literature uses occupation code or industry codes from the census, but I need to build another index because of the small range of occupations economists would work at. I define the occupations in the following ways: R1 university, all other university in U.S., research organization in the U.S., foreign institute, and private sector. The first occupation, R1 university, consists of 108 universities in the U.S. labeled as *Doctoral Universities: Very High Research Activity* in the Carnegie Classification of Institutions of Higher Education. The second occupation, all other universities in the U.S., is the collection of all other universities in the U.S. The third occupation, research organization in the U.S., is the list of research organizations in the U.S. listed in 2004 rankings of economics research institutions available at *econphd.net* and the U.S. governmental agencies. The fourth occupation, foreign institutes, consists of international schools, research organization, and governmental agencies. The last occupation, private sector, is the collection of all other remaining institutions.

The main difference between the first two occupations is teaching loads for faculties. According to the 2004 National Study of Post secondary Faculty, faculties in non-doctoral granting universities spend more time teaching than doctoral universities.¹⁵ The occupation of research organization in the U.S. does not require teaching, and the research goal would not be the same as the universities. The occupation of foreign institutes would be different from the U.S. counterparts. Each country has different institutional settings, and most international universities have different promotion policies than the U.S. (Smeets, Warzynski, and Coupé 2006). The firms in the private sector occupations would require different skills than other occupations. I count the words in all the job descriptions in JOE

14. If gender is not observable, I approximate it based on the first name.

15. See appendix Table B.2

and the advisory letters from Committee on the Status of Women in the Economics Profession.¹⁶ I examine the frequency of the words in each occupation. In every occupation, the words *research* and *economics* are frequently observed. Some words related to communication are commonly observed in private sectors but rarely observed in academic positions. That is, the required skills would be different for the private sectors.

The descriptive statistic for the sample is presented in Table 1. Compared to Table 1 in Oyer (2006), the sample compositions have evolved. As opposed to the late 1990s, the individuals in the sample have become increasingly foreign and more female. The different compositions raise the question of whether any findings below, vary systematically by gender and nationality. Additionally, I divide the sample by Ph.D. program rankings. In column (2), I subsample the individuals who graduated from 1–10 programs. Column (3) consists of the graduates from 11–23, and column (4) is taken from 24–45 programs. Graduates from lower-ranked programs (better quality programs) are more likely male, achieve more bachelor’s degrees in the U.S., publish more academic papers, and are more likely to be placed in academic jobs. Summary statistics for graduates’ fields of study are given in appendix Table B.1.

The demand for economists is compiled from the listings on JOE each year. All members of the American Economic Association have a professional obligation to list their job openings in JOE.¹⁷ Jobs are posted every month except January and July. JOE consists of six sections: full-time academic positions in the U.S., part-time academic positions, full-time international academic positions, part-time international academic positions, full-time non-academic positions, and part-time non-academic positions. Figure 1 presents the trend of the number of listings and unemployment rate over time. The number of postings would be a good proxy for a market demand that the job market candidate would face. Each panel includes the U.S. unemployment rate as of October in a previous year for another demand proxy, since the candidate starts the job search at least one year before graduation.

The left panel shows the total number of postings by an academic year.¹⁸ The trend is normalized based on 2004. Over the years, the unemployment rate started to rise in 2008, peaked in 2010, and moved down after, and the JOE listings generally moved in the opposite direction. The right panel dissects the patterns of JOE by job categories of the full-time positions. Note that they are a fraction of the total number of postings based in

16. The letters include the information on what female economists do in the jobs such as central banks or consulting firms in detail.

17. Minutes for the Annual Meeting, December 29, 1974, American Economic Review, Proceedings, May 1975, p. 443.

18. Duplicated entries are counted separately.

2010. *academic in US* is the fraction of the total postings into full-time academic postings in the U.S. *top 50* is the fraction of the total postings into full-time academic postings in top 50 universities in the U.S., *non academic in US* is the fraction of the total postings into full-time non-academic postings in the U.S. All proxies follow the unemployment rate in opposite ways with different degrees. The number of postings in both academic and non-academic sectors grew between 2004 and 2008. The full-time academic postings in the U.S. have the largest share and fluctuate considerably, but the demand from the elite schools seems relatively intact.

5 EMPIRICAL STRATEGY

In the previous sections, the model predicts that the effect of entry conditions would be permanent if economists acquire task-specific human capital. In the following sections, I analyze the placement outcomes, occupational choice, publication records, and mobility to examine the effects of entry conditions. In this section, I describe the estimation strategy to identify them both in the short run and the long run.

5.1 ESTIMATION THE SHORT-TERM AND LONG-TERM EFFECTS OF INITIAL LABOR MARKET CONDITIONS

I approximate entry conditions on the labor market using the unemployment rate as of October at the one year before graduation. I begin by estimating the effect of the entry conditions on the placement outcomes. The outcome variable for an individual i of graduating cohort c from department d with fields of study f is determined by the following linear model:

$$y_{icdf} = \beta ec_c + \gamma X_i + \lambda_d + \theta_f + \epsilon_{icdf} \quad (7)$$

in which λ_d and θ_f are fixed effects for department and fields of study, respectively. ec_c is an economic condition a cohort c face at their labor market entry. X_i includes an indicator for receiving bachelor's degrees in the U.S. and a gender indicator. ϵ_{icdf} is the error term presenting the remaining unobserved determinants of the outcome. Department fixed effects, λ_d , capture time-invariant department characteristics which lead to permanent shifts in career paths for the department's graduates. Fields of study fixed effects, θ_f , are necessary since job prospects, and the following career would be dependent on what the new graduates majored in. As the main regressor ec_c varies by cohort, standard errors are clustered by graduation cohort.

I start by investigating whether one would be landed at R1 university as a full-time assistant professor given that most economics Ph.D. are research oriented. Another dependent variable is the ranking of the placements to measure the entry effects on the quality of the placements. To examine the long-term impact, I further investigate whether one would work at R1 university 5 and 9 years after graduation separately using the same specification. I do not use the panel regression since the entry conditions mainly affect the first placements rather than multi-period effects. When analyzing job mobility, I focus on the cumulative status rather than on annual changes, as these variables present little year-to-year variation. I collapse multi waves of the panel into a single cross-section and estimate the same specification. The outcome variables include whether an individual has ever switched an occupation or a firm from the initial placements.

Next, I turn to analyze the effect of entry conditions on the economists' productivity. I approximate the economists' productivity using the cumulative number of publications in economics journals. The outcome variable for an individual i of graduating cohort c from department d with fields of study f at year t is determined by the following linear model:

$$y_{icdft} = \beta ec_c + \gamma X_i + \lambda_d + \theta_f + \tau_{exp} + \epsilon_{icdft} \quad (8)$$

in which λ_d and θ_f are fixed effects for department and fields of study, respectively. I further include the labor market experience fixed effects τ_{exp} where exp represents the number of years of experience.¹⁹ It is necessary to pick up the average effect of experience on the outcome variable. The dependent variable includes the cumulative number of articles in the top 50, top 20, and top 5 economics journals according to *IDEAS/RePEc Simple Impact Factors for Journals*.

Both specifications raise the question of the heterogeneous effect of entry conditions. The effects of a recession would be heterogeneous by gender since men and women face different circumstances when making decisions related to work, family, and household finances. The effects would be heterogeneous by nationality since foreign graduate students would have a different perspective on careers and work under the unique institutional policies. Also, the effects would be heterogeneous by department rank and fields of majors. I examine these effects employing a range of interaction terms with ec_c .

The last point of interest in heterogeneity is whether the effects of the entry conditions on the outcomes would vary by years of experience. Following Kahn (2010) and

19. The primary analysis is based on one's dissertation information or resume. Unlike CPS or other microdata, my data record the exact year of graduation and almost complete employment history. Literature tends to employ Mincerian specification to proxy potential experience, but I use actual experience since they are observable.

Oreopoulos, von Wachter, and Heisz (2012), I regress the outcome on the entry economic conditions for cohort c and the same control in (8) with department, field of study, and labor market experience fixed effects as following:

$$y_{icdft} = \sum_e \beta_e e c \cdot E_{i,exp} + \gamma X_i + \lambda_d + \theta_f + \tau_{exp} + \epsilon_{icdft} \quad (9)$$

where e denotes the number of years of experience after graduation. $E_{i,exp}$ is a binary variable indicating i 's year of experience. The coefficients of interest are the β_e 's, which describe the change in the experience profiles caused by the difference in the unemployment rate at graduation. I allow the effect to vary by each year of experience.

5.2 ENDOGENEITY

Several identifying assumptions are necessary. First, the effects of β would be unbiased as long as the average quality of economists entering the market is not systematically related to the state of the economy. That is, the specifications (7) and (8) treat the time of labor market entry as exogenous. However, the job market candidates might extend their years of study in order to avoid bad conditions at entry or enter early to benefit from favorable market conditions. The norm of the years of education for economic Ph.D. is five, and some might prolong their years into six or seven due to the market conditions. If the graduates delay graduation based on the entry economic conditions, the composition of the cohort would be different in bad economic conditions. I conducted a range of robustness checks in section 6.5 but could not find evidence to support this claim.

The last concern for the specifications is endogenous migration before and after graduation according to literature. People might migrate into the regions in response to local labor market conditions around the time of labor market entry. However, this is of less concern for economists since the job matching mostly takes place at the Allied Social Science Associations (ASSA), a three-day meeting each January in one place, a few months before graduation.

6 ESTIMATION RESULTS

6.1 PREDICTION 1: INITIAL PLACEMENTS

I first test whether the entry economic conditions predict the initial placement outcomes. I use the specification (7) to explore these connections in more detail in Table 2. Note

that Theorem 1 implies that a mismatch between a worker and occupation would arise when the entry condition is unfavorable. According to Assumption 1, most graduates are research-oriented, and hence the mismatch would mean that the individuals are less likely assigned to the research tasks. The dependent variable is whether the individual held a tenure track position in R1 university.

The negative coefficient on unemployment indicates that, on average, the graduates are less likely to get hired by R1 university when the macroeconomic conditions at graduation are relatively bad. The -0.0214 coefficient on unemployment in the first column implies that when unemployment increases by one standard deviation (2.04 percentage points), the graduates would be 9.14 percentage points less likely to hold an assistant professorship in R1 university than it otherwise would have. The coefficient on the female indicator is positive but statistically insignificant while obtaining a bachelor's degree in the U.S. is associated with a greater likelihood of working in R1 university.

The result in column (1) raises the questions on whether the entry effect would have a heterogeneous impact within the sample. I examine whether the Ph.D. program rankings would lead to a differential effect of entry conditions on the placement outcomes.²⁰ I convert the program rankings into a categorical variable, *tier*. Tier 1, tier 2, and tier 3 indicate the top 1–10, 11–23, and 24–45 programs. In column (2), instead of department fixed effects, I add the categorical variable interacted with unemployment. The coefficients on tier 2 and tier 3 are negative and statistically significant, implying that the graduates from tier 1 programs would have a premium on the academic placements. Note that the coefficients on the interaction terms are positive but insignificant so that there would be no differential effect for the graduates from tier 2 and tier 3 programs. Column (3) controls for the continuous variable of the Ph.D. program ranking *program rank* instead of the categorical variable and presents a similar result.

While I do not find the effect of being female on the placement outcomes and the differential effect of unemployment onto female graduates' placement outcomes in column (4), the entry condition would have a differential impact on those who achieved bachelor's degrees in the U.S. In all columns, the coefficient on *US bachelor degree* is positive and statistically significant, meaning that achieving the U.S. bachelor's degree would have an advantage over those who earn the degrees outside the U.S. In column (5), the coefficient on the interaction term further presents that the entry conditions would have less impact for U.S. degree holders. The joint F-test shows that the entry economic conditions would not affect the R1 placements for the U.S. degree holders. It is not surprising given that the graduates from the U.S. institutions would be better prepared for working at the U.S.

20. The rankings are quoted from *econphd.net rankings 2004*.

institutions such as possessing language skills or their visa status. Also, the economic downturn would make international students try to find jobs outside the U.S. Therefore, the entry conditions would have differential impacts.

I now focus on academic careers and test for the effect of entry economic conditions on the quality of the placements. From Table B.2 in appendix, faculties in doctoral universities tend to spend more time in research than non-doctoral universities, and similar patterns are observed within the doctoral universities. The more prestigious schools would have a better environment for research, and hence a research-oriented graduate would want to be placed at the top-quality institutions to accumulate research skills. I approximate the quality of the placements as the ranking of the placements. The sample includes those who started their career at R1 university. If the placement is not ranked, I rank it 350. If one's position is not full-time, I rank it 400 regardless of the placements (Ge, Wu, and Zhou 2021). The dependent variable is the ranking of the placements. I use the specification (7) to examine these relationships in Table 3. The positive coefficient on unemployment indicates that, on average, the graduates are more likely placed at the low-quality (higher-ranked) university in R1 when the economic conditions at graduation went bad, and the relationship is significant at 5 percent level. An increase in 1 standard deviation in the unemployment rate increases the placement ranking by 12.3 on average. Similar to Table 2, graduates from tier 1 programs would have a premium on the quality of placement (likely hired by the better-quality schools), but there would be no differential effect on the placement quality by program tiers. Similarly, I do not find the effect of being female on the quality of the placement and the differential impact of unemployment on female placements in column (4). Compared to Table 2, there is no advantage on having a U.S. bachelor's degree. Still, the entry conditions would have a differential impact on the quality for U.S. bachelor's degree holders in column (5) as in Table 2.

From Table 2 I find that the entry conditions would negatively affect the placement outcomes at R1 university. Given that most graduates are research-oriented, the bad entry conditions would result in an occupational mismatch. Table 3 further presents that the quality of the placement even within the R1 university placements is also lowered by the bad economic conditions. Note that faculties in more prestigious institutions tend to spend less time teaching (Noser, Manakyan, and Tanner 1996). It would imply that the terrible entry conditions would result in the task mismatch even within R1 university compared to good entry conditions.

6.2 PREDICTION 2: LONG-RUN PLACEMENTS

Next, I test whether the entry economic conditions predict one's career trajectory. The model predicts that one would not likely switch the occupation if one developed task-specific human capital in (6). Since I find the occupational mismatch in the beginning during the economic downturn, it is natural to ask whether the affected individuals would stay at their initial placements. I use the same specification (7) to examine whether one works at R1 university 5 and 9 years after graduation as an extension of the previous findings. Comparing the coefficients on unemployment between columns (1)–(3) in Table 4, it shows that the entry economic conditions have a negative and statistically significant effect on the R1 placement at the moments, but the magnitude declines over time compared to the impact on the initial placement. It might imply that graduates would switch occupations from the initial placements, but it would not be enough to overcome the mismatch driven by the entry conditions. To examine whether the entry effects would vary by the Ph.D. program rankings, I add the categorical variable *tier* and interact with unemployment in columns (4)–(6). I still find that the tier 1 programs graduates are more likely to work at R1 universities than graduates from tier 2 and tier 3 programs. Still, there would not be a differential effect of entry conditions in the long run.

One might raise the question as to whether the entry condition would serve as a signal of ability, and if its importance as a signal would decline over time as more information of actual ability is revealed. To test whether the effect of unemployment is getting weaker over time, I perform the regression based on the specification (9) in Table 5, but the results do not demonstrate waning effect over time. In column (1), instead, unemployment would have adverse effects up until five years after graduation with similar magnitude. Five years later, the magnitude is roughly similar while it is no longer significant. I add a binary variable indicating whether one's initial placement is R1 university in column (2). The coefficients on all the interaction terms are not significant, and the regression model explains better the variability of the outcome. It would imply that the subsequent occupational choices would be mainly driven by the first placement instead of the signaling effect.

6.3 PREDICTION 3: PUBLICATIONS

I now turn to analyze the effect of entry economic conditions on the research productivity. The main measures of research output for academic economists are the publication records. Success in academic jobs is mainly dependent on the number of scholarly publications. Most economics departments in doctoral universities place high value quality

publications, and tenure decisions would be based on the number of publications on top journals (Heckman and Moktan 2020). I select the top 50 economics journals from *IDEAS/RePEc Simple Impact Factors for Journals*.²¹ The dependent variable in the subsection is the cumulative number of articles published in the top 50 economics journals. I use the specification (8) to explore how the entry conditions would affect the economists' publication records in Table 6.

The first four columns use the full samples. The negative coefficient on unemployment in column (1) indicates that, on average, the individuals are less likely to publish the articles in the top 50 economics journals when entry economic conditions worsen, and the estimate is significant at a 5 percent level. The -0.0213 coefficient on unemployment implies that an increase in 1 standard deviation in unemployment rate at graduation would result in 2.31 percent fewer publications for the graduated cohorts. The negative coefficient on being female is not surprising since literature finds that female workers would underachieve in academic careers in which long-term human-capital investment is required (Finkel, Olswang, and She 1994).

I further examine whether the ranking of the Ph.D. programs would lead to heterogeneous effects of entry conditions on the publication outcomes. As before, I add the categorical variable *tier* and interact with the unemployment rate in column (2). The magnitude of the coefficient on unemployment is about 3.7 times larger in absolute value and statistically significant at any level. Both tier 2 and tier 3 graduates publish fewer journals than tier 1 graduates on average, and the coefficients on interaction terms imply that the entry conditions differentially impact them. In other words, the entry conditions would mainly affect the productivity of the graduates from the tier 1 programs compared to other tier graduates. In column (3), I examine the differential effect of the entry conditions on the female graduate's publication records. Female graduates would publish fewer publications than male graduates, but the interaction term is positive and statistically significant at any level. It would imply that the entry conditions would mainly affect the productivity of the male graduates compared to female graduates. I find no differential impact of having U.S. degrees on the publications.

Columns (5)–(8) examine those who started their careers at R1 university using the same specification. I find similar findings compared to columns (1)–(4), but the size of the coefficients on unemployment increases in absolute value. In columns (2) and (6), I find that the entry conditions would mainly affect tier 1 graduates' publication records. One possible explanation is that placements in R1 are very tough for graduates in tier 2 and tier 3 programs. Hence, if the individuals from tier 2 or tier 3 programs were landed at aca-

21. I do not include invitation-only journals and proceedings journals.

ademic placements during the bad economic times, they would be outstanding students. In other words, the dire economic conditions would positively select the best students from tier 2 or tier 3 programs, and their publications records would represent their qualities in part. Therefore, the entry conditions would not lower their publication records compared to tier 1 graduates.

The findings are in line with the model's predictions. Column (1) presents that the bad entry conditions would lead to a loss in economists' research productivity over their careers. Table 2 shows that the entry conditions would result in an occupational mismatch. The model predicts that if economists develop task-specific human capital, occupational switching would be costly. So, even if the bad conditions would make them start at the undesirable occupation, they would not be likely to switch, and hence, the effect of mismatch would remain in the long run. Column (5) indicates that entry conditions would lead to productivity loss even to those placed in R1 university. Some might argue that those who started their careers at R1 university during bad economic times would be positively selected. However, the finding in column (5) would confirm my model. Table 3 presents that the entry conditions would lead to lower quality placements in R1. The lower-quality institutions tend to require more teaching load to their faculties, and hence the human capitals the recessionary cohorts accumulate would be different from or undesirable from the surrounding cohorts who started at R1 university. The academic profession would discourage early switching than any other occupations economists possibly could work. Hence, the bad entry conditions would have left permanent effects on the economists' careers, as the model predicts in section 3. In appendix B.5 and B.6, I examine the number of publications in the top 20 and top 5 journals. The findings are similar for the top 20 and 50 publications, but I find no significant effect for the top 5 publications.

6.4 VALIDATING THE MODEL

The mechanism driving the permanent effect of entry conditions in the model is the job mobility of individuals. Workers tend to solve the initial mismatch problem by switching jobs. I argue that economists acquire task-specific skills in the occupations, making the economists unwilling to switch occupations. The empirical findings in the previous subsections show that the entry conditions would lead to the initial mismatches and that the effects remain significant even in the long run.

I analyze the transition probabilities from the initial occupation to the occupation nine years after graduation in Table 7 for overview. I select two cohorts from the good and

bad times each to see whether the patterns are notably different. Panel a summarizes the whole samples, panel b summarizes the good cohorts, and panel c summarizes the bad cohorts. In every occupation, more than 64 percent of individuals stay at the initial occupation 9 years after graduation. It is unusually high rates compared to other U.S. workers or inflexible markets such as the Netherlands (Topel and Ward 1992; van den Berge 2018). I do not find notable differences between the cohorts, and it might imply the switching patterns are hardly dependent on the entry conditions for economists.

In this subsection, I empirically test whether the entry economic conditions would affect one's mobility decision. I focus on the cumulative status rather than on changes by year because these variables show little year-to-year variation. The outcome of interest is whether one ever switches a job within years after graduation. The estimation is based on the specification (7) and Table 8 summarize the results for both occupation and firm switching decision. Switching firms or occupations for individuals is defined as working at different firms or occupations in year t compared to year $t - 1$. All firms belong to occupations, so individuals can only switch occupations if they also switch a firm. Note that the occupations can be divided into five categories: R1 university, all other universities in the U.S., research organization or governmental agency in the U.S., foreign institute, and private sector. I collapse multiple waves of the panel into a single cross-section and estimate the same specification. For column (1), the dependent variable is whether one ever switches the occupation within three years after graduation. Columns (2) and (3) summarize the result within six and nine years after graduation. Columns (4)–(6) summarize the result for the firm switching.

The insignificant estimates on unemployment in columns (1)–(3) support the model's predictions in which one would not likely switch an occupation based on entry economic conditions. The estimates in columns (4)–(6) follow the model as well since the model predicts that if one switched a job, it would happen early, and the tasks should be similar. The entry economic conditions would likely make individuals switch a firm within three years after graduation. The significance of the estimates tends to go away over time. Since I find no evidence of occupation switching, the switched firm would be under the same occupations. Since all firms within the same occupation have almost the same tasks, those who switched a firm within the occupation accumulate similar task-specific human capital as before. Hence, the negative shock leads to the occupational mismatch, and the effect would remain over one's career.

It is natural to ask whether the individuals who started at R1 university would not switch when the entry conditions worsen. This is because I find the task mismatch in Table 3 and the permanent effect in column 5 in Table 5. I perform the same estimation using

the individuals who started their career at full-time positions in R1 university in Table 9. I find no effect on occupational switching and no effect on firm switching within three and six years after graduation. Column (6) shows that the entry conditions would affect the individuals to switch a firm within nine years after graduation. However, column (3) would imply the switching would happen within the same occupation, so the empirical findings are still in line with the model's predictions.

6.5 ROBUSTNESS CHECK

In the analysis above, I assumed that the macroeconomic conditions at the time of graduation represent an exogenous labor demand shock. That is, I assume the average quality of graduates who enter the market is not systematically associated with the economic conditions. Note that the five years of study is arguably the norm of the economics Ph.D. programs. My data allows me to examine whether graduates adjust their timing of graduation to labor market conditions partially. I observe the duration of the study for 60 percent of the sample (see Figure 3). Based on the specification (7), I examine the effect of the entry economic conditions on one's decision to delay graduation in Table 10.

The dependent variable is an indicator of whether one studies longer than five years in Ph.D. programs. The estimates in all columns except column (2) present that the entry conditions would not affect graduation timing on average. In column (2), instead of department fixed effects, I add the categorical variable *tier* and create an interaction with unemployment. Then, the coefficient on unemployment is positive and significant at the 10 percent level. It might imply that the entry conditions would lead to delay in the graduation. And, the joint F-tests to examine whether the total effects are equal to zero for tier 2 and tier 3 graduates show that they are less likely to get affected by the entry conditions. It raises the concern on whether the entry conditions would only affect tier 1 graduates, although the t-tests for both interaction terms are not significant. However, it makes sense intuitively because the extra years of study are costly for the Ph.D. programs, and therefore only selected programs could afford it to their students.

If the individuals in tier 1 programs would have options to delay graduations, the quality of graduates from the tier 1 programs would be associated with the entry conditions. To test this conjecture, I re-run the regressions using the samples without the individuals from tier 1 programs in Table 11. In column (1), the dependent variable is whether the initial placement is at R1 university as in Table 2. Column (2) examines the effect of entry conditions on the ranking of the placements as in Table 3. Column (3) examines the cumulative number of publications in the top 50 economics journals. Column (5)–(8)

examines the early career change as in Table 9. The magnitudes of the coefficients are changed slightly, but the result is not much different from the original regressions.

7 CONCLUSION

This paper examines whether the entry economic conditions would impact economists' careers and productivity over a period. The model is developed based on task-specific human capital formation and supplies the intuition of job mobility. The model further reveals that the individuals would not be willing to switch occupations even though they had a poor match with the initial occupations. The second half of the paper empirically tests the model's predictions. I find that demand for economists is largely pro-cyclical. Second, the economic downturn would lead to initial mismatches. Third, the effect would remain more than nine years after graduation, but the effect declines over time. The recessionary cohorts are less likely to work at R1 university and publish fewer articles in the top 50 economics journals. I further examine their job mobility and find that the entry conditions would not affect the occupational switching. These findings indicate that the economics Ph.D.s accumulate task-specific human capital; the occupations are highly specialized.

Indeed, the analysis cannot be marked for a complete understanding of research objectives. The research is based on the individuals' C.V. or resume, which is entirely subjective. It is possible that those who post a complete C.V. would be more successful economists. Also, the research has inherent attribution problems. However, assuming that those missing individuals are less likely successful, I believe my findings would provide the minimum effects of the entry conditions on the economics Ph.D.'s career and productivity. To conclude, the transition from education to the labor market in a recession would threaten the economists' careers. Their occupational outlook would not be more promising than surrounding cohorts, and the productivity loss is expected on average.

Table 1: Descriptive statistics of Graduates by Department Rankings

	Overall (1)	tier 1 (2)	tier 2 (3)	tier 3 (4)
Main independent variables				
female	0.287 (0.452)	0.251 (0.433)	0.324 (0.468)	0.309 (0.462)
US bachelor	0.426 (0.494)	0.471 (0.499)	0.398 (0.489)	0.376 (0.484)
Main outcome variables				
number of publications by 3 years	0.327 (0.742)	0.445 (0.873)	0.247 (0.627)	0.210 (0.557)
number of publications by 6 years	0.873 (1.516)	1.208 (1.778)	0.641 (1.298)	0.546 (1.048)
number of publications by 9 years	1.414 (2.325)	1.970 (2.748)	1.020 (1.948)	0.880 (1.562)
Initial placements				
tenure-track in R1 university	0.232 (0.422)	0.301 (0.459)	0.184 (0.388)	0.165 (0.371)
private Sector	0.240 (0.427)	0.226 (0.418)	0.261 (0.439)	0.241 (0.427)
number of schools	32	10	10	12
number of individuals	3,979	1,795	1,197	987

I collect the job market candidates from 32 universities in the US and group them into three categories by department rankings. The ranks are quoted from *econphd.net rankings 2004*. Column (2), (3) and (4) summarize those who graduated from 1–10, 11–23, 24–45 departments in the US, respectively. I count the number of cumulative publications from the top 50 economics journals for the primary analysis. Job mobility reports the probability of switching a job from the initial placement. Standard errors are in parentheses.

Table 2: The effect of economic conditions at graduation on the initial placement in R1 universities

	(1)	(2)	(3)	(4)	(5)
unemployment (β_u)	-0.0214*** (0.00483)	-0.0286** (0.0106)	-0.0278* (0.0135)	-0.0172** (0.00654)	-0.0317*** (0.00612)
female	0.00616 (0.0160)	0.00570 (0.0149)	0.00193 (0.0150)	0.00586 (0.0149)	0.00618 (0.0161)
US bachelor degree	0.0589*** (0.0109)	0.0657*** (0.0118)	0.0664*** (0.0122)	0.0588*** (0.0109)	0.0587*** (0.00877)
tier 2		-0.114*** (0.0145)			
tier 3		-0.128*** (0.0193)			
unemployment \times tier 2 (β_1)		0.0168 (0.0151)			
unemployment \times tier 3 (β_2)		0.00897 (0.0180)			
program rank			-0.00425*** (0.000794)		
unemployment \times program rank (β_1)			0.000448 (0.000704)		
unemployment \times female (β_1)				-0.0144 (0.0148)	
unemployment \times US bachelor degree (β_1)					0.0234*** (0.00664)
$\beta_u + \beta_1$		-0.0118		-0.0316	-0.0082
P-val from F-test $\beta_u + \beta_1 = 0$		0.3335		0.0259	0.1803
$\beta_u + \beta_2$		-0.0196			
P-val from F-test $\beta_u + \beta_2 = 0$		0.0980			
mean(dependent variable)	0.2339	0.2339	0.2339	0.2339	0.2339
Observations	3916	3916	3916	3916	3916
R ²	0.063	0.040	0.034	0.063	0.064

Standard errors in parentheses and are clustered by cohort level.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

The dependent variable is whether one holds a full-time position at R1 university at graduation. Estimates are based on Eq. (7), and department and fields of study fixed effects are included in the estimation except column (2) and (3). Column (2) and (3) include field of study fixed effects only. *tier 2* and *tier 3* are binary variable indicating whether one graduated from 11–23 ranked departments and 24–45 ranked departments, respectively. *Program rank* is a continuous variable indicating the rank of the PhD programs.

Table 3: The effect of economic conditions at graduation on the ranking of the initial placement for those who placed in R1 university

	(1)	(2)	(3)	(4)	(5)
unemployment (β_u)	12.30** (4.590)	12.63* (5.725)	14.28* (6.312)	12.45* (5.463)	24.51** (8.556)
female	0.458 (11.54)	0.273 (9.472)	0.777 (9.478)	0.418 (11.47)	1.622 (11.26)
US bachelor degree	14.77 (10.79)	15.27 (11.84)	16.25 (11.36)	14.79 (10.71)	13.95 (8.691)
tier 2		42.13*** (7.503)			
tier 3		68.10*** (11.02)			
unemployment \times tier 2 (β_1)		-4.003 (6.936)			
unemployment \times tier 3 (β_2)		-3.320 (11.26)			
program rank			2.205*** (0.355)		
unemployment \times program rank (β_1)			-0.270 (0.325)		
unemployment \times female (β_1)				-0.531 (8.717)	
unemployment \times US bachelor degree (β_1)					-22.36** (9.337)
$\beta_u + \beta_1$		8.6290		11.9195	2.1511
P-val from F-test $\beta_u + \beta_1 = 0$		0.1906		0.1418	0.5991
$\beta_u + \beta_2$		9.3116			
P-val from F-test $\beta_u + \beta_2 = 0$		0.4121			
mean(dependent variable)	137.80	137.80	137.80	137.80	137.80
Observations	1183	1183	1183	1183	1183
R ²	0.125	0.081	0.075	0.125	0.129

Standard errors in parentheses and are clustered by cohort level.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

The dependent variable is the ranking of the placement. The department ranks are quoted from *econphd.net rankings 2004*. Estimates are based on Eq. (7), and the estimation only includes those who started their career from full-time positions in R1 university. If the placement is not ranked, I rank it 350. If one's position is not full-time, I rank it 400 regardless of the placements Ge, Wu, and Zhou (2021). I include department and fields of study fixed effects except column (2) because column (2) controls the rank of the programs. *tier 2* and *tier 3* are binary variable indicating whether one graduated from 11–23 ranked departments and 24–45 ranked departments, respectively. *Program rank* is a continuous variable indicating the rank of the Ph.D. programs.

Table 4: The effect of entry conditions on the placement in R1 university over time

	(1) initial	(2) 5 years	(3) 9 years	(4) initial	(5) 5 years	(6) 9 years
unemployment (β_u)	-0.0214*** (0.00483)	-0.0121* (0.00595)	-0.00821* (0.00434)	-0.0286** (0.0106)	-0.0110 (0.00659)	-0.00583 (0.00773)
female	0.00616 (0.0160)	-0.00878 (0.0161)	-0.0182* (0.00930)	0.00570 (0.0149)	-0.00828 (0.0153)	-0.0151 (0.00846)
US bachelor degree	0.0589*** (0.0109)	0.103*** (0.00947)	0.106*** (0.0148)	0.0657*** (0.0118)	0.115*** (0.00963)	0.123*** (0.0133)
tier 2				-0.114*** (0.0145)	-0.136*** (0.0171)	-0.118*** (0.0204)
tier 3				-0.128*** (0.0193)	-0.138*** (0.0187)	-0.115*** (0.0180)
unemployment \times tier 2 (β_1)				0.0168 (0.0151)	0.00537 (0.0175)	0.00415 (0.0206)
unemployment \times tier 3 (β_2)				0.00897 (0.0180)	-0.00890 (0.0161)	-0.0123 (0.0163)
$\beta_u + \beta_1$				-0.0118	-0.0056	-0.0016
P-val from F-test $\beta_u + \beta_1 = 0$				0.3335	0.7185	0.9127
$\beta_u + \beta_2$				-0.0196	-0.0199	-0.0181
P-val from F-test $\beta_u + \beta_2 = 0$				0.0980	0.1077	0.1453
mean(dependent variable)	0.2339	0.3069	0.2788	0.2339	0.3069	0.2788
Observations	3916	3916	3916	3916	3916	3916
R ²	0.063	0.064	0.065	0.040	0.046	0.045

Standard errors in parentheses and are clustered by cohort level.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

Estimates are based on Eq. (7), and field of study fixed effect is included in all the estimations. Columns (1)–(3) further includes department fixed effects. The dependent variable in columns (1) and (4) is whether one works at R1 university at graduation. The dependent variable in columns (2) and (5) is whether one works at R1 university five years after graduation. The dependent variable in columns (3) and (6) is whether one works at R1 university nine years after graduation. *tier 2* and *tier 3* are binary variable indicating whether one graduated from 11–23 ranked departments and 24–45 ranked departments, respectively.

Table 5: The signaling effect of unemployment on the placement outcomes over time

	(1)	(2)
unemployment \times exp 0–1 years	-0.0146** (0.00608)	0.00115 (0.00409)
unemployment \times exp 2–3 years	-0.0122* (0.00565)	0.00355 (0.00482)
unemployment \times exp 4–5 years	-0.0115* (0.00578)	0.00425 (0.00535)
unemployment \times exp 6–7 years	-0.00770 (0.00510)	0.00801 (0.00555)
unemployment \times exp 8–9 years	-0.00701 (0.00454)	0.00869 (0.00528)
female	-0.00672 (0.0139)	-0.0115 (0.00664)
US bachelor degree	0.100*** (0.00896)	0.0548*** (0.00809)
R1 university		0.773*** (0.00897)
Observations	19580	19580
R ²	0.063	0.541

Standard errors in parentheses and are clustered by cohort level.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

Estimates are based on Eq. (9), and the dependent variable is whether one works at the tenure-track position in R1 at time t . Department, fields of study, and labor market experience fixed effects are included in all estimations. *R1 university* is an indicator for whether one's initial placement is R1 university or not. *exp* is an indicator for whether one has a particular years of experience.

Table 6: The effect of economic conditions at graduation on the number of publications in Top 50 economics journals

	Full sample				Restricted to initial placement in R1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
unemployment (β_u)	-0.0213*** (0.00795)	-0.0807*** (0.0244)	-0.0452*** (0.0119)	-0.0136 (0.00915)	-0.0628** (0.0252)	-0.0886*** (0.0306)	-0.110*** (0.0307)	-0.0273 (0.0291)
female	-0.288*** (0.0240)	-0.278*** (0.0239)	-0.286*** (0.0226)	-0.288*** (0.0240)	-0.576*** (0.0563)	-0.558*** (0.0526)	-0.555*** (0.0583)	-0.571*** (0.0572)
US bachelor degree	0.00424 (0.0119)	0.0594*** (0.0123)	0.00448 (0.0120)	0.00435 (0.0116)	-0.00749 (0.0638)	0.0821 (0.0506)	-0.0165 (0.0640)	-0.0127 (0.0619)
tier 2		-0.609*** (0.0485)				-0.902*** (0.0838)		
tier 3		-0.685*** (0.0537)				-0.860*** (0.0774)		
unemployment \times tier 2 (β_1)		0.104*** (0.0363)				0.149** (0.0671)		
unemployment \times tier 3 (β_2)		0.104** (0.0435)				-0.0215 (0.0646)		
unemployment \times female (β_1)			0.0817*** (0.0216)				0.167** (0.0706)	
unemployment \times US bachelor degree (β_1)				-0.0175 (0.0111)				-0.0645 (0.0431)
$\beta_u + \beta_1$		0.0234	0.0365	-0.0311		0.0608	0.0570	-0.0918
P-val from F-test $\beta_u + \beta_1 = 0$		0.1456	0.0108	0.0031		0.2241	0.3325	0.0124
$\beta_u + \beta_2$		0.0229				-0.1100		
P-val from F-test $\beta_u + \beta_2 = 0$		0.2951				0.0254		
mean(dependent variable)	0.9225	0.9225	0.9225	0.9225	1.9321	1.9321	1.9321	1.9321
Observations	50311	50311	50311	50311	11963	11963	11963	11963
R ²	0.169	0.149	0.169	0.169	0.324	0.298	0.325	0.324

Standard errors in parentheses and are clustered by cohort level and current year t.

* p < 0.10, ** p < .05, *** p < .01

Estimates are based on Eq. (8) and the dependent variable is the cumulative number publications in the top 50 economics journals. The journal rankings are quoted from *IDEAS/RePEc Simple Impact Factors for Journals*. I include field of study and department fixed effects in all estimations except columns (2) and (6) because they control for the program tiers explicitly. Column (5)–(8) summarize the results for those who started their career at R1 university.

Table 7: Transition Probability between Occupations

Initial occupation	occupation 9 years after graduation				
	R1 university	all other US university	research org in US	foreign institute	private institute
panel a. all samples					
R1 university	74.08	5.08	6.37	8.21	6.26
all other US university	10	73.04	4.13	4.57	8.26
research org in US	11.67	3.24	67.91	4.86	12.32
foreign institute	6.31	2.87	3.78	77.87	9.17
private institute	6.17	2.54	6.89	7.01	77.39
panel b. cohorts from 07 and 08 (good cohorts)					
R1 university	74.78	3.04	6.96	9.57	5.65
all other US university	8.73	77.78	1.59	3.97	7.94
research org in US	10.34	2.59	69.83	5.17	12.07
foreign institute	7.36	1.84	0.61	77.91	12.27
private institute	5.94	1.83	9.13	7.31	75.8
panel c. cohorts from 10 and 11 (bad cohorts)					
R1 university	74.21	4.74	6.32	5.79	8.95
all other US university	8.89	76.67	5.57	1.11	7.78
research org in US	11.8	2.25	64.04	6.18	15.73
foreign institute	8.48	3.57	3.57	76.34	8.04
private institute	4.68	2.92	10.53	5.85	76.02

Each row calculates the transition probabilities from the initial occupation to the occupation working at 9 years after graduation.

Table 8: The Effect of Entry Conditions on the Job Mobility

	Occupational switching			Firm switching		
	(1)	(2)	(3)	(4)	(5)	(6)
	≤ 3 years	≤ 6 years	≤ 9 years	≤ 3 years	≤ 6 years	≤ 9 years
unemployment	-0.00238 (0.00595)	0.00166 (0.00842)	-0.00216 (0.00939)	0.0151*** (0.00398)	0.0121 (0.00949)	0.00694 (0.00774)
female	0.00586 (0.00675)	0.0250 (0.0170)	0.0108 (0.0176)	0.0182* (0.00795)	0.00573 (0.0161)	-0.00568 (0.0140)
US bachelor degree	0.000261 (0.00747)	-0.00796 (0.0106)	-0.0153 (0.0128)	0.0345* (0.0186)	0.0243 (0.0154)	0.00933 (0.0164)
mean(dependent variable)	0.1751	0.3133	0.4180	0.3199	0.5413	0.6912
Observations	3916	3916	3916	3916	3916	3916
R ²	0.019	0.021	0.015	0.023	0.017	0.014

Standard errors in parentheses and are clustered by cohort level.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

Estimates are based on Eq. (7), and department and fields of study fixed effects are included in the estimation. The dependent variable is a binary indicator for whether one switches the occupation or the firm from the initial placements. Column (1) summarizes whether one ever switches the occupation within 3 years after graduation. Column (2)–(3) summarize whether one ever switches the occupation within 6 years and 9 years after graduation. Column (4)–(6) summarize the result for the firm switching within 3, 6, and 9 years after graduation. Switching firms or occupations for individuals is defined as working at different firms or occupations in year t compared to year $t - 1$. All firms belong to occupations, so individuals can only switch occupations if they also switch a firm. Note that the occupations can be divided into five categories: R1 university, all other universities in the U.S., research organization or governmental agency in the U.S., foreign institute, and private sector.

Table 9: The Effect of Entry Conditions on the Job Mobility for those who started the career at R1 university

	Occupational switching			Firm switching		
	(1)	(2)	(3)	(4)	(5)	(6)
	≤ 3 years	≤ 6 years	≤ 9 years	≤ 3 years	≤ 6 years	≤ 9 years
unemployment	0.000915 (0.00449)	0.0145 (0.0104)	0.00544 (0.00974)	0.0136 (0.00974)	0.0199 (0.0118)	0.0263** (0.00961)
female	0.00703 (0.0154)	0.0651 (0.0378)	0.00702 (0.0311)	0.0250 (0.0283)	0.0512 (0.0407)	0.00889 (0.0344)
US bachelor degree	-0.00425 (0.0259)	-0.0187 (0.0283)	-0.0638 (0.0373)	0.0204 (0.0420)	-0.0229 (0.0325)	-0.0199 (0.0229)
mean(dependent variable)	0.0982	0.2128	0.3668	0.1855	0.3853	0.6233
Observations	916	916	916	916	916	916
R ²	0.060	0.056	0.066	0.046	0.071	0.066

Standard errors in parentheses and are clustered by cohort level.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

I include those who started their careers at a full-time position in R1 university. Estimates are based on Eq. (7), and department and fields of study fixed effects are included in the estimation. The dependent variable is a binary indicator for whether one switches the occupation or the firm from the initial placements. Column (1) summarizes whether one ever switches the occupation within 3 years after graduation. Column (2)–(3) summarize whether one ever switches the occupation within 6 years and 9 years after graduation. Column (4)–(6) summarize the result for the firm switching within 3, 6, and 9 years after graduation. Switching firms or occupations for individuals is defined as working at different firms or occupations in year t compared to year $t - 1$. All firms belong to occupations, so individuals can only switch occupations if they also switch a firm. Note that the occupations can be divided into five categories: R1 university, all other universities in the U.S., research organization or governmental agency in the U.S., foreign institute, and private sector.

Table 10: The effect of economic conditions on delaying graduation

	(1)	(2)	(3)	(4)	(5)
unemployment (β_u)	0.0247 (0.0136)	0.0485* (0.0240)	0.0478 (0.0324)	0.0243 (0.0167)	0.0213 (0.0159)
female	0.0202 (0.0149)	0.00958 (0.0155)	0.0105 (0.0152)	0.0202 (0.0151)	0.0202 (0.0148)
US bachelor degree	-0.0218 (0.0356)	-0.0255 (0.0357)	-0.0266 (0.0356)	-0.0218 (0.0355)	-0.0220 (0.0355)
tier 2		0.0102 (0.0282)			
tier 3		-0.0172 (0.0397)			
unemployment \times tier 2 (β_1)		-0.0276 (0.0166)			
unemployment \times tier 3 (β_2)		-0.0592 (0.0447)			
program rank			-0.000741 (0.00139)		
unemployment \times program rank (β_1)			-0.00144 (0.00156)		
unemployment \times female (β_1)				0.00143 (0.0165)	
unemployment \times US bachelor degree (β_1)					0.00804 (0.0295)
$\beta_u + \beta_1$		0.0209		0.0257	0.0292
P-val from F-test $\beta_u + \beta_1 = 0$		0.2423		0.0741	0.2612
$\beta_u + \beta_2$		-0.0106			
P-val from F-test $\beta_u + \beta_2 = 0$		0.7128			
mean(dependent variable)	0.4909	0.4048	0.4048	0.4909	0.4909
Observations	2371	2371	2371	2371	2371
R ²	0.069	0.027	0.025	0.069	0.069

Standard errors in parentheses and are clustered by cohort level.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

Estimates are based on Eq. (7), and department and fields of study fixed effects are included in the estimation except column (2) and (3). Only fields of study fixed effect is included in column (2) and (3). The dependent variable is whether one studied longer than 5 years. The samples are limited since the records of the starting year of Ph.D. are partial. *tier 2* and *tier 3* are binary variable indicating whether one graduated from 11–23 ranked departments and 24–45 ranked departments, respectively.

Table 11: Robustness Check: Regressions without graduates from tier 1 programs

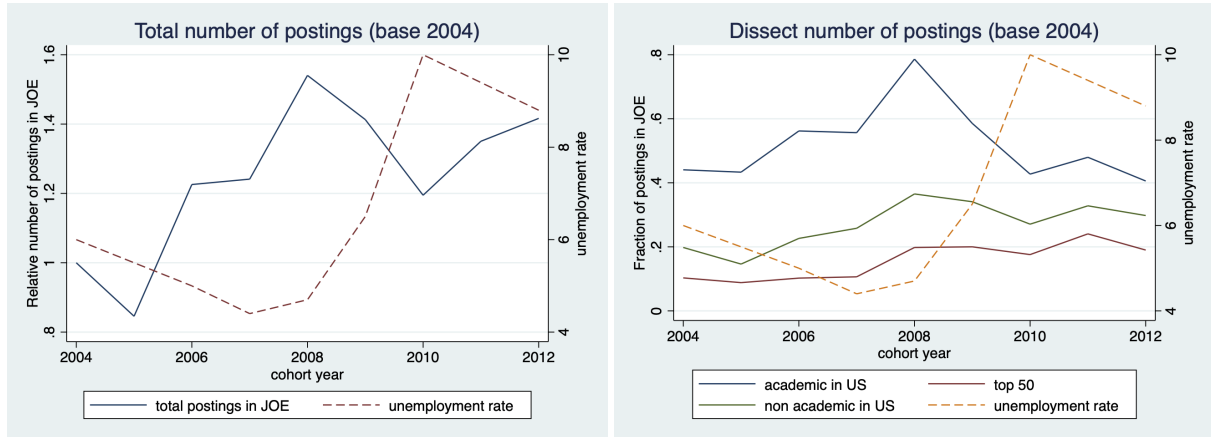
	(1) R1 university SR	(2) placement rank	(3) R1 university LR	(4) Top 50 publications	(5) OC switching ≤ 3 yrs	(6) OC switching ≤ 6 yrs	(7) FR switching ≤ 3 yrs	(8) FR switching ≤ 6 yrs
unemployment	-0.0173** (0.00737)	13.74** (5.373)	-0.00821* (0.00434)	-0.0317*** (0.00751)	-0.0108 (0.00996)	-0.00749 (0.0137)	0.00695 (0.00886)	0.00737 (0.0141)
female	0.0189 (0.0105)	-8.914 (15.22)	-0.0182* (0.00930)	-0.221*** (0.0206)	0.0250 (0.0145)	0.0474* (0.0216)	0.0407** (0.0146)	0.0400 (0.0228)
US bachelor degree	0.0642** (0.0259)	-9.229 (21.04)	0.106*** (0.0148)	-0.0903*** (0.0205)	-0.0125 (0.00782)	-0.00294 (0.0188)	0.0214 (0.0200)	0.0360 (0.0299)
Observations	2148	507	3916	27552	2148	2148	2148	2148
R ²	0.053	0.145	0.065	0.128	0.028	0.031	0.033	0.027

Standard errors in parentheses clustered by cohort and current year t .

* $p < 0.10$, ** $p < .05$, *** $p < .01$

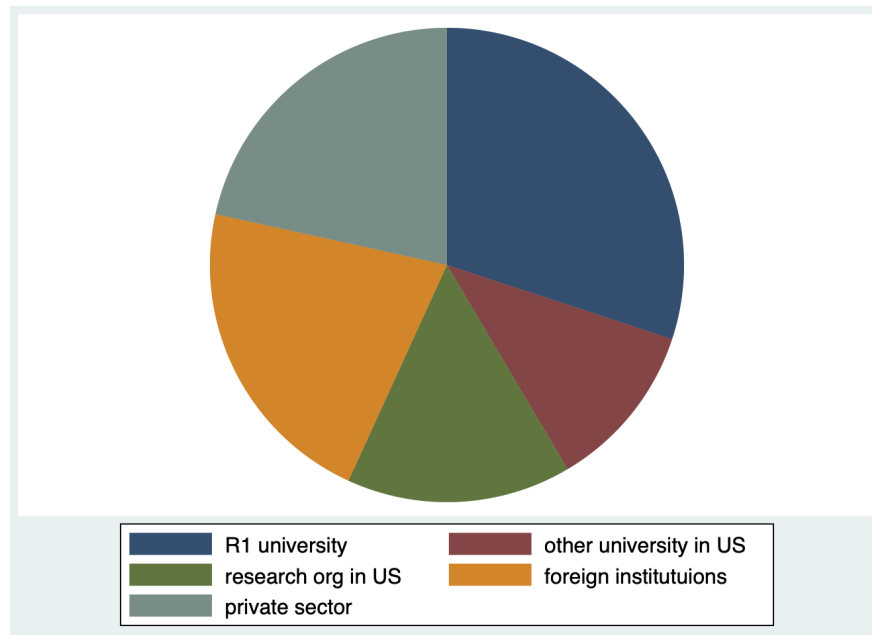
Estimates in column (1) and (2) are based on Eq. (7), and department and fields of study fixed effects are included in the estimation. The dependent variable for column (1) is whether one started the career in R1 university. The dependent variable for column (2) is the placement rank as in Table 3. The dependent variable for column (3) is whether one works at R1 university 9 years after graduation. Estimates in column (4) are based on Eq. (8), and department, fields of study and labor market experience fixed effects are included in the estimation. The dependent variable is the number of cumulative publications in the top 50 economics journals. Estimates in column (5)–(8) are based on Eq. (7), and department and fields of study fixed effects are included in the estimation similar to Table 9. The dependent variable is whether one ever switches occupation or firm within 3 and 6 years after graduation. Switching firms or occupations for individuals is defined as working at different firms or occupations in year t compared to year $t - 1$. All firms belong to occupations, so individuals can only switch occupations if they also switch a firm. Note that the occupations can be divided into five categories: R1 university, all other universities in the U.S., research organization or governmental agency in the U.S., foreign institute, and private sector.

Figure 1: Macroeconomic Conditions and JOE Listings



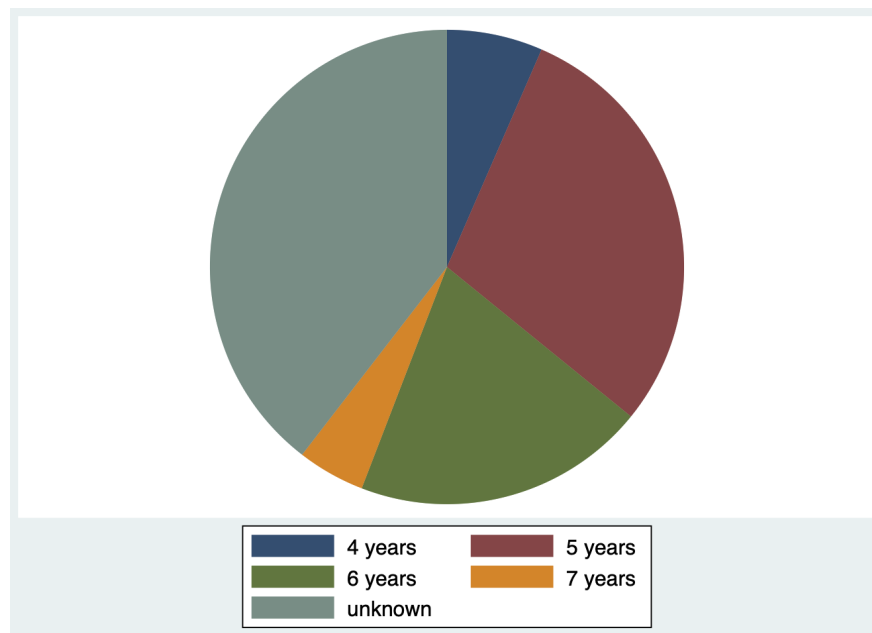
For the left panel, *total postings in JOE* is the number of postings in JOE by an academic year, and unemployment rate is the U.S. unemployment rate as of October. The former is normalized so that 2004 = 1. The right panel dissects the number of total postings. *academic in US* is the fraction of the total postings into full-time academic postings in US. *top 50* is the fraction of the total postings into full-time academic postings in top 50 universities in U.S. *non academic in US* is the fraction of the total postings into full-time non-academic postings in US. Note that all the numbers in the right panel except unemployment rate is normalized based on 2004.

Figure 2: Distribution of the Initial Placements



The figure summarizes the distribution of initial placements. The percent of R1 university, other university in US, research organization in US, international institutes and private sectors are: 30%, 11%, 15%, 22%, 22%

Figure 3: Distribution of the Year of Study



The figure summarizes the availability of years of study.

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APPENDIX

A TECHNICAL APPENDIX

A wide range of matching algorithms is necessary for this project. ProQuest provides limited information on individuals, and I need to find their C.V.s, Linkedin profiles, and publication records. From the employment records, I need to assign the occupation and rankings according to the reference. Since the matching keywords are very limited, I need to borrow the advanced techniques from data science literature. Since data include identifiable information on individuals, I do not provide the actual data or the relevant code, but this section will guide you on how to acquire them.

A.1 DATA RETRIEVAL

ProQuest provides a search tool for finding dissertations. Authorized users can extract the name of the authors, Ph.D. institutions, degree date, advisor names, title, abstract, and range of classifications. Unfortunately, the authors' department information is available after class of 2013, so I use advisor's information if the classification code does not include economics (0501). I use *googlesearch* library in Python to extract advisors' information whether they are faculty members in the economics department.

From the name of authors, name of Ph.D. institution and degree date, I try to find C.V., resume, individual websites, or Linkedin addresses. I extract 20 pages for each individual²² and try to find the most matched one.

A.2 FUZZY STRING MATCHING

Finding the right match is notoriously difficult in this setting. The problem consists of trying to match similar but different words (or strings in types of computer language), for example, *LeBron James* or *Lebron R James* or *UC Berkeley* or *University of California, Berkeley*. This type of problem is called *fuzzy string matching* in natural language procession (NLP) literature. Python provides a range of libraries to handle the issue.

The basic algorithm is as follows. First, the strings need to be modified to make the strings comparable. From this process, all unnecessary characters are removed, and the strings are at least comparable. For example, make the strings lowercase or remove the

22. I use *googlesearch* and *Scale SERP*, Google Search Results API. *googlesearch* often causes HTTP errors such as 429 especially when the users have too many requests. *Scale SERP* provides fast and almost error-free results but cost \$0.29 per 1000 pages.

special characters like ., *, —. Second, find a metric to measure the similarity between the strings. The metric is sometimes called the distance, which will determine the degree of similarity between the strings. Third, set the threshold for the right match between 0–1. This step is necessary if we do not know whether there is a correct match.

The concept of Levenshtein Distance is one of the most popular metrics to measure the distance among the strings. It calculates the number of necessary edits to transform one string to another. The edits mean adding a new letter, removing a letter, or replacing a letter. The metric formula is easily found in any reference on the web.²³ There are many ways to transform the words to be matched, but Levenshtein Distance arguably selects the shortest path.

The name matching is like sentence matching since names consist of multiple strings. That is, it requires vectorizing a name and needs to have a vector search for finding the most similar vectors. Term Frequency Inverse Document Frequency Vectorization (or TF-IDF) is a popular approach used in NLP applications, approximating the relevance of a word in a sentence, paragraph, or whole document. It counts the frequency of each string and assigns a vector of weights for each word. From the basic algorithm, one needs to partition the strings into N-gram and then perform TF-IDF vectorization. Once the vector of weights of N-grams is calculated, possible to measure the similarity between the names.

23. For example, https://en.wikipedia.org/wiki/Levenshtein_distance

B MORE ESTIMATIONS

I further test whether the entry condition would have differential impact on the placement outcomes by one's field of study. I divide the samples into Micro and Macro using the JEL classification of the dissertation. For macro, I include G (Finance), E (Macroeconomics and Monetary Economics) and F (International Economics). For micro, I include J (Labor), I (Health and Education), D (Microeconomics), K (Law and Economics), L (Industrial Organization), R (Urban), O (Agriculture) and H (Public Economics). I use the specification (7) and perform the regression on the subsamples of Macro, Micro, and JEL classifications in Table B.4. Note that the dependent variable is whether one is hired in R1 university. I find the significant coefficients as in Table 2 for the Micro group and some micro-related JEL classifications. This is in part because financial sectors and international organizations demand macro-related fields more than micro.

Table B.1: Descriptive statistics of Graduates by JEL classifications

JEL classificaitons	fields of study	rank 1 (%)	rank 2 (%)	rank 3 (%)
G	Financial Economics	27.05	27.47	22.01
J	Labor	18.27	21.46	18.29
D	Microeconomics	9.13	9.71	8.79
I	Health, Education	8.16	7.03	7.44
C	Mathemathical methods	6.15	3.89	5.86
M	Business	5.17	3.89	4.59
E	Macroeconomics	5.00	7.31	7.68
F	International Economics	4.42	5.00	5.94
O	Development	3.73	2.78	2.93
H	Public	2.99	2.96	2.53
L	IO	2.81	2.13	2.77
Q	Agriculture and Environment	2.47	2.59	5.15
K	Law	0.92	0.56	0.40
R	Urban	0.92	1.11	2.61
N	History	0.69	0.65	0.55
P	Economic System	0.63	0.19	0.40

To classify fields of study, I use grduates' ProQuest dissertation information: title, classification code, abstracts, identifiers, and subjects. See appendix for technical details. The each column summariz those who graduated from 1–9, 10–19, 20–45 departments in U.S., respectively.

Table B.2: Classes: hours per week teaching credit classes

	1-3 hours (%)	4-7 hours (%)	More than 7 hours (%)
Estimates			
Total	22.4	27.8	49.8
Institution: level			
2-year	18.3	23.7	58
4-year non-doctoral granting	18.6	23.5	57.9
4-year doctoral granting	27.4	33.1	39.6

Source: U.S. Department of Education, National Center for Education Statistics, 2004 National Study of Post secondary Faculty

Table B.3: The effect of entry conditions on the initial placement: multinomial logit

	(1)	(2)
2. all other universities		
unemployment	-0.106** (0.0454)	-0.0838* (0.0499)
3. research org		
unemployment	0.138** (0.0663)	0.134** (0.0630)
4. foreign institute		
unemployment	0.188*** (0.0431)	0.188*** (0.0447)
5. private sectors		
unemployment	-0.0247 (0.0403)	-0.0181 (0.0364)
FX		department, fields of study
Observations	3979	3916

Base is R1 university

Gender and US bachelor degrees are controlled.

Standard errors in parentheses and are clustered by cohort level.

* $p < 0.10$, ** $p < .05$, *** $p < .01$

Table B.4: The effect of initial labor market conditions on the initial placement by Fields of Study

	(1) Macro	(2) Micro	(3) JEL G Finance	(4) JEL J Labor	(5) JEL D Micro	(6) JEL I Health	(7) JEL E Macro	(8) JEL C Quant	(9) JEL F International	(10) JEL M Business	(11) JEL Q Agri	(12) JEL O Dev	(13) JEL H Public	(14) JEL L IO
unemployment	-0.0207 (0.0127)	-0.0328*** (0.00484)	-0.00619 (0.0153)	-0.0110** (0.00475)	-0.0460** (0.0144)	-0.0240* (0.0117)	-0.0199 (0.0217)	0.0102 (0.0348)	-0.0957** (0.0308)	0.00496 (0.0205)	-0.0270 (0.0386)	-0.0164 (0.0309)	-0.00465 (0.0513)	-0.0580 (0.0313)
female	0.00610 (0.0207)	0.0228 (0.0180)	-0.00477 (0.0338)	0.0181 (0.0355)	-0.00904 (0.0562)	0.0702 (0.0426)	0.00385 (0.0861)	0.0658 (0.0933)	0.0481 (0.0681)	-0.188 (0.105)	-0.154* (0.0746)	0.0740 (0.102)	-0.132 (0.0829)	0.00611 (0.126)
US bachelor degree	0.0358 (0.0278)	0.0676*** (0.0179)	0.0450 (0.0342)	0.0660*** (0.0189)	-0.0261 (0.0619)	0.148** (0.0555)	-0.00840 (0.0566)	0.0159 (0.0558)	-0.00288 (0.0472)	0.0957* (0.0500)	0.0643 (0.0862)	0.0535 (0.0884)	0.269* (0.128)	0.0678 (0.121)
Observations	1484	1859	1019	766	363	301	259	217	205	176	128	123	104	99
R ²	0.069	0.062	0.075	0.081	0.117	0.142	0.136	0.183	0.192	0.166	0.339	0.199	0.292	0.363

Standard errors in parentheses and are clustered by cohort level.

* p < 0.10, ** p < .05, *** p < .01

Estimates are based on Eq. (7), and department fixed effect is also included in the estimation. The column (1) and (2) summarize macro and micro related fields. For macro, I include G (Finance), E (Macroeconomics and Monetary Economics) and F (International Economics). For micro, I include J (Labor), I (Health and Education), D (Microeconomics), K (Law and Economics), L (Industrial Organization), R (Urban), O (Agriculture) and H (Public Economics).

Table B.5: The effect of economic conditions at graduation on the number of publications in Top 20 economics journals

	Full sample				Restricted to initial placement in R1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
unemployment (β_u)	-0.0128*** (0.00487)	-0.0560*** (0.0181)	-0.0240*** (0.00788)	-0.00553 (0.00617)	-0.0293 (0.0189)	-0.0751*** (0.0268)	-0.0574** (0.0246)	-0.0129 (0.0253)
female	-0.159*** (0.0145)	-0.152*** (0.0144)	-0.158*** (0.0143)	-0.159*** (0.0145)	-0.408*** (0.0372)	-0.400*** (0.0341)	-0.396*** (0.0391)	-0.406*** (0.0371)
US bachelor degree	-0.0286*** (0.0102)	0.0200** (0.00903)	-0.0285*** (0.0103)	-0.0285*** (0.00992)	-0.203*** (0.0420)	-0.0996*** (0.0356)	-0.208*** (0.0418)	-0.205*** (0.0408)
tier 2		-0.462*** (0.0356)				-0.792*** (0.0688)		
tier 3		-0.487*** (0.0374)				-0.778*** (0.0664)		
unemployment \times tier 2 (β_1)		0.0684** (0.0285)				0.150*** (0.0539)		
unemployment \times tier 3 (β_2)		0.0745** (0.0328)				0.0658 (0.0608)		
unemployment \times female (β_1)			0.0385** (0.0169)				0.0994* (0.0519)	
unemployment \times US bachelor degree (β_1)				-0.0165** (0.00736)				-0.0300 (0.0370)
$\beta_u + \beta_1$		0.0123	0.0144	-0.0219		0.0746	0.0420	-0.0428
P-val from F-test $\beta_u + \beta_1 = 0$		0.3150	0.2094	0.0004		0.0430	0.3043	0.1187
$\beta_u + \beta_2$		0.0185				-0.0093		
P-val from F-test $\beta_u + \beta_2 = 0$		0.2637				0.8279		
mean(dependent variable)	0.5094	0.5094	0.5094	0.5094	1.2222	1.2222	1.2222	1.2222
Observations	50311	50311	50311	50311	11963	11963	11963	11963
R ²	0.131	0.113	0.131	0.131	0.274	0.245	0.275	0.275

Standard errors in parentheses and are clustered by cohort level and current year t.

* p < 0.10, ** p < .05, *** p < .01

Estimates are based on Eq. (8) and the dependent variable is the cumulative number publications in the top 20 economics journals. The journal rankings are quoted from *IDEAS/RePEc Simple Impact Factors for Journals*. I include field of study and department fixed effects in all estimations except columns (2) and (6) because they control for the program tiers explicitly. Column (5)–(8) summarize the results for those who started their career at R1 university.

Table B.6: The effect of economic conditions at graduation on the number of publications in Top 5 economics journals

	Full sample				Restricted to initial placement in R1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
unemployment (β_u)	-0.00339 (0.00232)	-0.0216** (0.00987)	-0.00523 (0.00396)	-0.00209 (0.00244)	0.0128 (0.00781)	0.000553 (0.0173)	0.00992 (0.0128)	0.0101 (0.0121)
female	-0.0813*** (0.00786)	-0.0756*** (0.00750)	-0.0812*** (0.00785)	-0.0813*** (0.00786)	-0.193*** (0.0211)	-0.167*** (0.0181)	-0.192*** (0.0218)	-0.193*** (0.0211)
US bachelor degree	-0.00680 (0.00422)	0.0225*** (0.00426)	-0.00678 (0.00423)	-0.00678 (0.00418)	-0.103*** (0.0213)	-0.0435** (0.0167)	-0.103*** (0.0210)	-0.102*** (0.0207)
tier 2		-0.243*** (0.0184)				-0.504*** (0.0424)		
tier 3		-0.261*** (0.0193)				-0.490*** (0.0391)		
unemployment \times tier 2 (β_1)		0.0302** (0.0151)				0.0717** (0.0324)		
unemployment \times tier 3 (β_2)		0.0299* (0.0171)				0.0144 (0.0369)		
unemployment \times female (β_1)			0.00629 (0.00723)				0.0103 (0.0247)	
unemployment \times US bachelor degree (β_1)				-0.00296 (0.00362)				0.00495 (0.0158)
$\beta_u + \beta_1$		0.0085	0.0010	-0.0050		0.0722	0.0201	0.0150
P-val from F-test $\beta_u + \beta_1 = 0$		0.1973	0.7985	0.1475		0.0003	0.1910	0.1398
$\beta_u + \beta_2$		0.0082				0.0149		
P-val from F-test $\beta_u + \beta_2 = 0$		0.2726				0.4804		
mean(dependent variable)	0.1842	0.1842	0.1842	0.1842	0.4633	0.4633	0.4633	0.4633
Observations	50311	50311	50311	50311	11963	11963	11963	11963
R ²	0.097	0.077	0.097	0.097	0.192	0.159	0.192	0.192

Standard errors in parentheses and are clustered by cohort level and current year t.

* p < 0.10, ** p < .05, *** p < .01

Estimates are based on Eq. (8) and the dependent variable is the cumulative number publications in the top 5 economics journals. The journal rankings are quoted from *IDEAS/RePEc Simple Impact Factors for Journals*. I include field of study and department fixed effects in all estimations except columns (2) and (6) because they control for the program tiers explicitly. Column (5)–(8) summarize the results for those who started their career at R1 university.

C MATHEMATICAL DERIVATION

Proposition 1:

From the specification (4), consider the task tenure Task_{iot} in two-task model

$$\begin{aligned}\text{Task}_{\text{iot}} &= \rho_o \left[\beta_o^R H_{\text{it}}^R + (1 - \beta_o^R) H_{\text{it}}^T \right] \\ &= \rho_o \left[\beta_o^R \beta_{o'}^R \text{Exp}_{\text{io}'t} + (1 - \beta_o^R) (1 - \beta_{o'}^R) \text{Exp}_{\text{io}'t} \right] \\ &= \rho_o \left[\beta_o^R \beta_{o'}^R + (1 - \beta_o^R) (1 - \beta_{o'}^R) \right] \text{Exp}_{\text{io}'t}\end{aligned}$$

Using the partial derivative with respect to β_o^R yields

$$\rho_o \left\{ \beta_{o'}^R + (-1) (1 - \beta_{o'}^R) \right\} = \rho_o (-1 + 2\beta_{o'}^R)$$

Hence, given that $\rho_o > 0$,

$\beta_{o'}^R > 0.5$ implies $\frac{\partial \text{Task}_{\text{iot}}}{\partial \beta_o^R} > 0$,

$\beta_{o'}^R < 0.5$ implies $\frac{\partial \text{Task}_{\text{iot}}}{\partial \beta_o^R} < 0$, and

$\beta_{o'}^R = 0.5$ implies $\frac{\partial \text{Task}_{\text{iot}}}{\partial \beta_o^R} = 0$

Occupational choice in (6):

$$Y_{\text{ifot}} - x_{\text{io}'t} - Y_{\text{if}'o't} = (m_{\text{io}} - m_{\text{io}'}) + (\mu_{\text{if}} - \mu_{\text{if}'}) + \rho_o \text{Task}_{\text{iot}} - \rho_{o'} \text{Task}_{\text{io}'t}$$

Then, $Y_{\text{ifot}} - x_{\text{io}'t} - Y_{\text{if}'o't} > 0$ implies

$$(m_{\text{io}} - m_{\text{io}'}) + (\mu_{\text{if}} - \mu_{\text{if}'}) + (\rho_o - \rho_{o'}) \text{Task}_{\text{io}'t} > \rho_o (\text{Task}_{\text{io}'t} - \text{Task}_{\text{iot}}) + x_{\text{io}'t}$$

Note that

$$\begin{aligned}\text{Task}_{\text{io}'t} - \text{Task}_{\text{iot}} &= \beta_{o'}^R H_{\text{it}}^R + (1 - \beta_{o'}^R) H_{\text{it}}^T - \left\{ \beta_o^R H_{\text{it}}^R + (1 - \beta_o^R) H_{\text{it}}^T \right\} \\ &= (\beta_{o'}^R - \beta_o^R) (H_{\text{it}}^R - H_{\text{it}}^T)\end{aligned}$$

Hence, $Y_{\text{ifot}} - x_{\text{io}'t} - Y_{\text{if}'o't} > 0$ implies

$$(m_{\text{io}} - m_{\text{io}'}) + (\mu_{\text{if}} - \mu_{\text{if}'}) + (\rho_o - \rho_{o'}) \text{Task}_{\text{io}'t} > (\beta_{o'}^R - \beta_o^R) (H_{\text{it}}^R - H_{\text{it}}^T) + x_{\text{io}'t}$$